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Viscosity Modeling of MES and SLS Using Machine Learning Method

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Abstract. Viscosity is crucial to improve the efficiency of injected fluids for oil displacement in reservoirs. Traditionally, research has focused on polymers that help reduce the mobility of injected fluids, while surfactant viscosity has received less consideration. This research investigated the viscosity behavior of methyl ester sulfonate (MES) and sodium lauryl sulfate (SLS) surfactant solutions using a machine learning method—adaptive neurofuzzy inference system (ANFIS). This study aimed to predict the viscosity of surfactant solutions. Experimental data included viscosity measurements of 36 MES and SLS samples at various concentrations and temperatures, obtained by digitizing viscosity curves. These data served as input and validation for the ANN and ANFIS models. The results showed that ANFIS predicted viscosity values reliably, yielding only 1.33% and 0.43% differences for MES and SLS, respectively. Comparison of viscosity prediction with Artificial Neural Network (ANN) showed that ANFIS prediction was better, because ANN yielded two deviating predictions.

Keywords: concentration, oil, surfactant, temperature, viscosity

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1. **Introduction**

Controlling the mobility of fluids injected into oil reservoirs is largely dependent on viscosity. The injected fluid should be less mobile than the oil it is intended to replace in order to effectively displace it. A fingering effect, in which the injected fluid prematurely penetrates the oil zone, may happen if the injected fluid has greater mobility than the oil. Poor sweep efficiency results from this, which lowers the oil recovery factor. Chemical additives like surfactants and polymers are added to the injected fluid to increase its viscosity in order to regulate fluid mobility. However, the concentration of these additives must be carefully optimized. While increasing viscosity helps reduce the injected fluid's mobility to desirable levels, excessive viscosity can have adverse effects. Highly viscous fluids require higher injection pressures, which can damage the reservoir formation and injection infrastructure. Moreover, too low a mobility may lead to the accumulation of chemical additives within rock pores, reducing both their concentration in the solution and the permeability of the reservoir [1-6].

While polymers are primarily used to increase the viscosity of injected fluid, surfactants mainly reduce interfacial tension between water-oil and alter wettability. Consequently, less attention has been given to surfactant viscosity, even though it can significantly influence oil displacement efficiency in reservoirs. Early studies in other fields demonstrated the diverse impacts of surfactants on viscosity. For instance, Hamill and Petersen (1966) showed that increasing the concentration of ammonia and AMP in an olive oil–glycerin system produced a stiffer interfacial layer and higher viscosity, linking viscosity changes to emulsion stability[7]. Similarly, Meban (1978) found that pulmonary surfactant films exhibited sharp viscosity increases with concentration but decreased viscosity at higher temperatures, suggesting structural shifts within the films [8].Later, Jansen et al. (2001) introduced the “depletion flow number” as a parameter to model the viscosity of emulsions stabilized by surfactants, especially under shear-thinning conditions [9].

Research since the mid-2000s has highlighted diverse factors influencing surfactant viscosity across systems. Gokul et al. (2005) reported unusual finding that solutions containing SHNC and EHAC showed viscosity increases with temperature, peaking before declining, linked to micelle elongation [10]. Lu et al. (2009) demonstrated that polymer additives altered pulmonary surfactant viscosity: nonionic polymers (PEG, dextran) reduced viscosity and improved lung distribution, while hyaluronan formed gel-like structures that stabilized but did not lower viscosity [11]. In enhanced oil recovery (EOR), Wang et al. (2010) revealed that optimal—not extreme—interfacial tension (IFT) and polymer viscosity maximized recovery in heterogeneous reservoirs, since ultralow IFT could trap emulsions [12]. Later, Esteves et al. (2016) showed concentration-dependent viscosity changes in surfactants like SA-9, SLS, and EH-14, while Nowak et al. linked surfactant-driven variations in viscosity and IFT to droplet coalescence behavior [13] [14]. Expanding this, Khademi et al. (2017) found that cationic, anionic, and zwitterionic surfactants significantly altered PMMA suspension viscosity through micelle formation and particle interactions, especially above the critical micelle concentration [15].

Recent studies from 2019 onward demonstrate the expanding scope of surfactant viscosity research across nanofluids, industrial systems, and EOR. Kaggwa et al. (2019) showed that surfactant choice strongly affects nanofluid viscosity and stability, with CTAB causing the largest viscosity rise, ARB ensuring long-term suspension, and SDBS maintaining Newtonian flow [16]. Wahyuni et al. (2020) highlighted Tween 80’s role in boosting asphalt emulsion viscosity, improving road durability [17]. Molchanov et al. (2021) reported rapid micelle growth and sharp viscosity increases in EHAC-based wormlike micelles under moderate salt concentrations, relevant for oil recovery and personal care products [18]. Herrada et al. (2022) found that surface viscosity steadies droplets under flow but reduces overall droplet stability at low capillary numbers [19]. Li and He (2023) modeled surfactant-covered liquid threads, showing strong stabilizing effects on viscoelastic dynamics with implications for microfluidics and printing [20]. Jin et al. (2023) explained parabolic viscosity–temperature behavior in surfactant systems, depending on surfactant type and hydration effects [21]. Nazdrajic et al. (2024) compared surfactant combinations in soaps, noting significant viscosity rises with DEA versus modest increases with APG [22]. Talapatra and Nojabaei (2024) used molecular dynamics to show that microemulsion viscosity depends nonlinearly on surfactant concentration, salinity, temperature, and pressure, with SDS enhancing viscosity stability [23]. More recently, Yousefrooz et al. (2025) developed grafted polymeric surfactants that act as both surfactant and polymer, achieving up to 57% higher oil recovery [24], while Fathaddin et al. (2025) applied machine learning to model viscosity in natural polymer–surfactant systems, confirming concentration and salinity as key factors [25].

The ANFIS model with an average absolute relative deviation (AARD, %) of 0.95 showed remarkable ability to predict the viscosity of fluids consisting of 12 ternary mixtures [26]. In 2017, Kassem et al. verified that the ANFIS was reliable and precise in forecasting the dynamic viscosity of blends of biodiesel [27]. In 2015, Eryilmaz et al. used artificial neural networks to model the kinematic viscosity of biodiesel derived from safflower and wild mustard. With a coefficient of determination of 0.9999, the ANN model was able to produce viscosity predictions that were extremely accurate [28]. The ANN model was used by Belmadani et al. in 2020 to simulate the kinematic viscosity of biodiesel. An experimental collection of 1025 points, comprising 34 systems—15 pure, 14 binary, and 5 ternary—was applied as the basis for the growth of this model. A correlation coefficient of 0.9653 was obtained from the prediction performance results [29]. This suggested that ANFIS and ANN were appropriate for modelling viscosity. A machine learning method inspired by the idea of a human neuron is called an artificial neural network [30]. The system consists of several interconnected processing units, known as neurons, that communicate with each other through synapses, or electromagnetic connections, and cooperate to solve problems. The neurons are arranged in layers and are intimately related. Data is received by the input layer, and the output layer produces the outcome. Between the two, one or more secret layers are typically inserted. With this configuration, estimating or knowing the precise data flow is difficult. ANFIS, on the other hand, combines neural networks and fuzzy logic systems [31] [32]. This model can learn nonlinear systems and complicated relationships using experimental or computational pattern data [33]. Based on the evidence mentioned above, the purpose of this work was to use ANN to model the sodium lauryl sulfate and methyl ester sulfonate viscosity based on the previously given information [34].

2. **Methods**

Figure 1 illustrates the overall research process. The experimental work involved preparing methyl ester sulfonate (MES) and sodium lauryl sulfate (SLS) solutions at a salinity of 5,000 ppm with concentrations varying from 0.5% to 3.0% and temperatures ranging from 30°C to 60°C. Table 1 presents the experimental settings for modeling the viscosity of MES and SLS solutions. Viscosity measurements for each sample were conducted using a rotational viscometer in triplicate to ensure accuracy and reproducibility. The measured data were then used to develop machine learning models based on Adaptive Neuro-Fuzzy Inference Systems.

The ANFIS model combined the learning capability of neural networks with the rule-based reasoning of fuzzy inference systems. In the ANFIS model, hybrid learning combining least squares and backpropagation was implemented with a tolerance for training error being set to 1×10^{-5}. Two input variables (temperature and concentration) were used, with viscosity as the single output. Sugeno-type inference system was used as Fuzzy inference type, while generalized bell-shaped membership functions (gbellmf) were employed for the fuzzification of the input variables. Nine fuzzy rules were generated based on the input–output mapping. Constant type and weighted average (wtaver) were used as output membership function and defuzzification method respectively. A hybrid learning algorithm, integrating least squares and backpropagation, was used for efficient parameter estimation. Root Mean Square Error less than 0.00001 was used to evaluate training performance. The model was trained for 1,000 epochs, ensuring convergence to stable prediction accuracy. Each epoch used a batch learning mode with all the training samples included in one iteration.

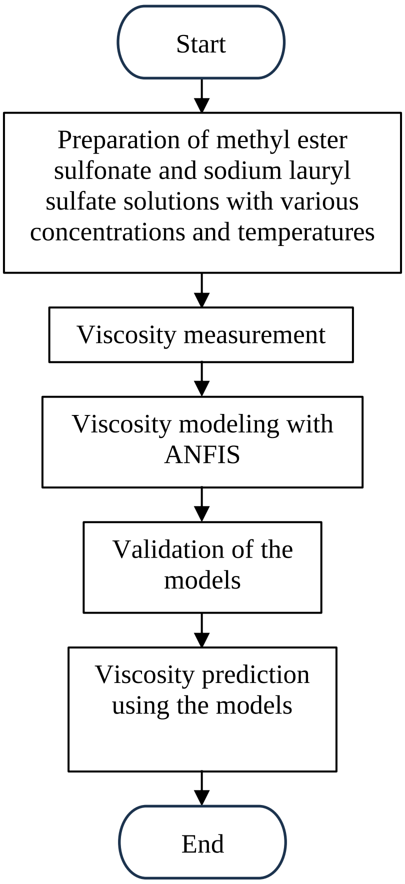

Figure 1. Research methodology

Table 1. Experimental Setting of the MES and SLS solution viscosity modeling research

Aspect	Description
Materials	MES and SLS surfactants in aqueous solutions (salinity 5000 ppm).
Concentration	0.5% – 3.0% (w/v).
Temperature	30°C – 60°C.
Measurement Instrument	Rotational viscometer
Data Acquisition	Viscosity curves digitized from experimental plots, resulting in 332 data points for MES and 277 for SLS.
Data Division	70% for training, 30% for testing; validation performed using experimental measurements.
Input Variables	Temperature (°C) and surfactant concentration (%).
Output Variable	Viscosity (cP).
Fuzzy Inference Type	First-order Sugeno-type inference system.
Membership Function Type	Generalized bell-shaped (gbellmf) membership functions for both inputs
Number of Fuzzy Rules	9 fuzzy rules generated from input–output mapping.
Learning Algorithm	Hybrid method combining least squares estimation and backpropagation.

Aspect	Description
Training Parameters	1000 epochs, tolerance = 1×10^{-5}, batch learning mode.
Comparison Model	Artificial Neural Network (ANN) — observed two minor deviations from measurement data.

Viscosity modeling was carried out using ANFIS, with two inputs: temperature and the concentrations of sodium lauryl sulfate and methyl ester sulfonate. The curve digitization data in Figures 2 and 3 served as the basis for the creation of the ANFIS models. To create a valid model, the ANFIS model was optimized. The correlation coefficient value was used to identify the model. The performance and validity of the ANFIS model was compared through analysis [34]. Following its validation, the ANFIS model was applied to forecast, within the limits of the measurement results, the viscosity values of sodium lauryl sulfate and methyl ester sulfonate solutions for a range of concentration and salinity values. Then the ANN model was used as a comparison to the ANFIS model.

3. Results and Discussion

Viscosity measurements were carried out three times for each methyl ester sulfonate and sodium lauryl sulfate solution. The measurements were performed using a rotational viscometer. Figure 2 displays the findings of the viscosity tests for different methyl ester sulfonate concentrations in solution and temperatures. In the meantime, Figure 3 displays the results of the viscosity test of sodium lauryl sulfate solution at various concentrations and temperatures.

Figure 2 illustrates that the methyl ester sulfonate solution's viscosity increased in direct proportion to concentration increases and inversely proportional to temperature increases. For every concentration and temperature variation examined, the average viscosity of the methyl ester sulfonate solution ranged from 1.49 cP to 2.03 cP. The viscosity of a surfactant solution increases with increasing concentration because more surfactant molecules are dissolved in water, causing them to interact more frequently and form micelles. As the concentration increases, the solution becomes denser and the movement of surfactant molecules becomes slower. Therefore, the solution becomes thicker and the viscosity increases. Conversely, a surfactant solution's viscosity is inversely proportional to temperature because rising temperatures cause the molecules' kinetic energy to rise as well, causing them to move more quickly and weakening the bonds between them. As a result, previously stable micelle-like structures begin to become more dynamic and easily crumbled, so the solution becomes thinner and the viscosity decreases.

The viscosity of sodium lauryl sulfate solution exhibits a similar relationship in Figure 3, where it is inversely proportional to temperature and directly proportional to concentration. For every concentration and salinity variation examined, the average viscosity of sodium lauryl sulfate solution ranged from 1.15 cP to 1.73 cP. For the range of concentrations and temperatures tested, the methyl ester sulfonate solution generally had a slightly lower viscosity than sodium lauryl sulfate, according to a comparison of Figures 2 and 3.

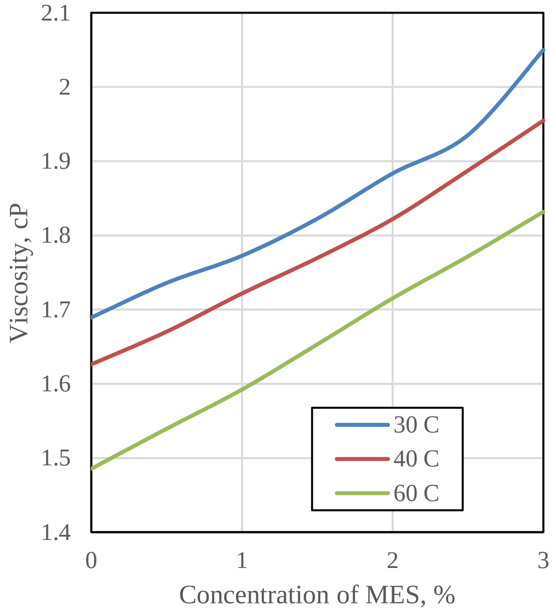

Figure 2. Viscosity of methyl ester sulfonate (MES) solution as a function of concentration and temperature

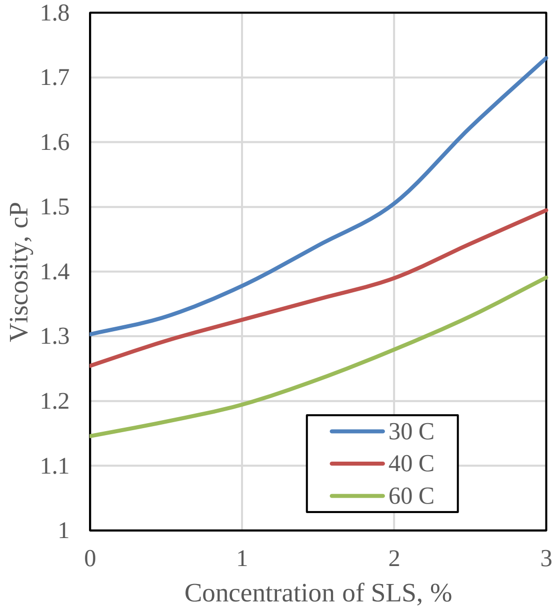

Figure 3. Viscosity of sodium lauryl sulfate (SLS) solution as a function of concentration and temperature

The data used for the ANFIS modeling were obtained by digitizing the curves in Figures 2 and 3. In this way, 332 data were obtained for modeling the viscosity of the methyl ester sulfonate solutions and 277 data for modeling the viscosity of the sodium lauryl sulfate solutions. In modeling, 70% of the digitized results were used for the training process, while the rest was used for the testing processes. The viscosity data of the methyl ester sulfonate solution and sodium lauryl sulfate solution obtained from the measurement results were used for validating the model.

Figure 4 shows the ANFIS structure for modeling viscosity correlations of the methyl ester sulfonate (MES) and sodium lauryl sulfate solutions (SLS). Several layers were used to build these models. Each layer contained several nodes consisting of adaptive nodes and fixed nodes. Adaptive nodes represented the set of parameters that can be adjusted in this node. In contrast, fixed nodes represented the set of parameters that were fixed in the model. The ANFIS structure used concentration and temperature variables (gray nodes) as input and one output, namely viscosity (purple nodes). The first layer was a fuzzification layer that converts the input into a fuzzy set through membership functions (mf) as depicted by the red nodes. In these viscosity models, generalized bell-shaped membership function (gbellmf) type was used. The second layer was a multiplication layer where the nodes function to be multiplied by the input signal to produce the output signal. Each blue node in this layer served to calculate the activation strength (firing power) of each rule as the product of all incoming inputs. The third layer was a defuzzification layer where each green node in this layer was an adjustable node. The fourth layer had only one yellow node. This layer served to aggregate all outputs on the third layer. Overall, the fourth layer built an adaptive network that was functionally equivalent to the first-order Sugeno fuzzy model. The ANFIS models were run with 1000 epochs. The smallest RSME in modeling methyl ester sulfonate and sodium lauryl sulfate solutions were 0.002165 and 0.003299, respectively.

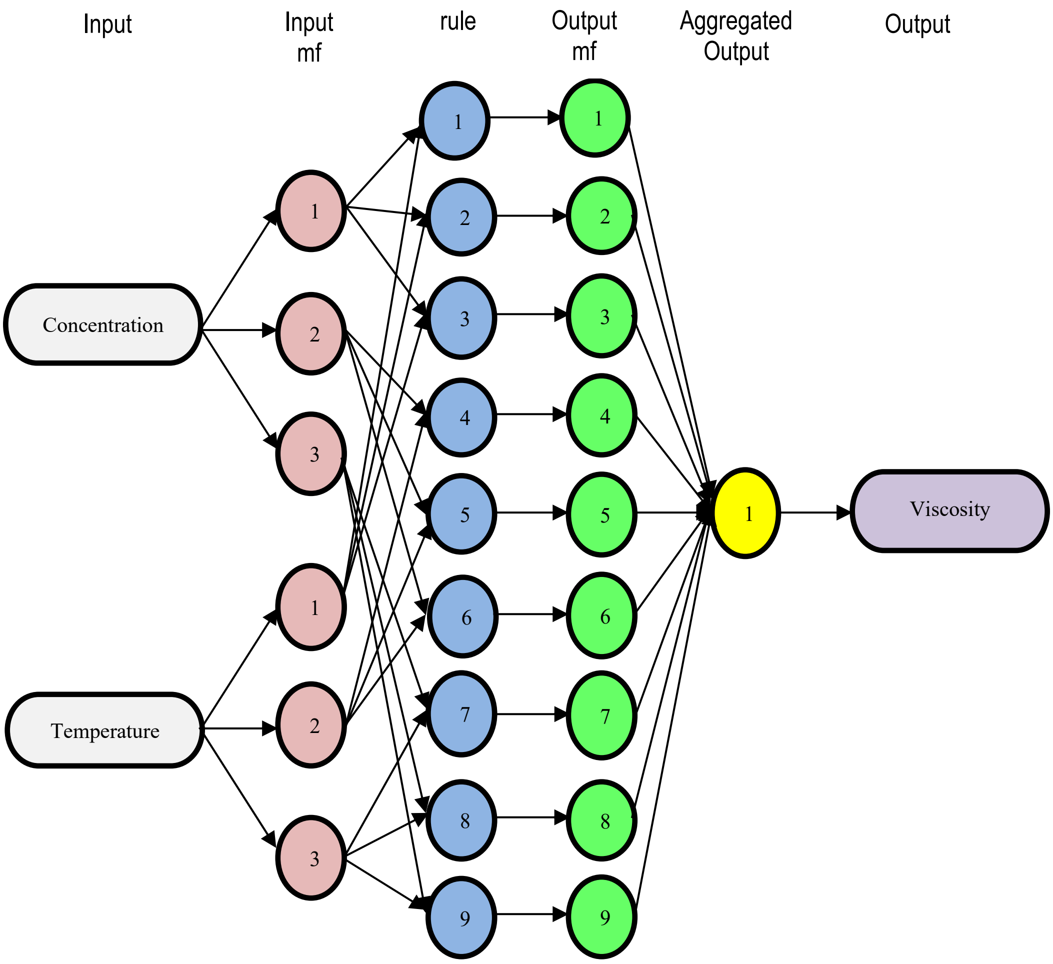

Figure 4. ANN structure for modeling MES and SLS solution viscosity correlation

Comparison of the model predictions with the data demonstrated the validity of the ANFIS model. Tables 2 and 3 show a comparison of the ANFIS models for the viscosity of methyl ester sulfonate and sodium lauryl sulfate solutions, respectively. Based on the tables, the correlation coefficient (r) between the ANFIS predictions and data for the viscosity of methyl ester sulfonate solutions was 0.99981 and that for the viscosity of sodium lauryl sulfate solutions was 0.99915. A high correlation coefficient value close to one indicates that all models make accurate predictions.

Table 2. Validation of ANFIS model for viscosity correlation of MES solution

No.	μ_{Data}, cP	μ_{ANFIS}, cP	No.	μ_{Data}, cP	μ_{ANFIS}, cP	No.	μ_{Data}, cP	μ_{ANFIS}, cP
1	1.69	1.69	8	1.63	1.63	15	1.49	1.48
2	1.74	1.73	9	1.67	1.67	16	1.54	1.54
3	1.77	1.78	10	1.72	1.72	17	1.59	1.59
4	1.82	1.82	11	1.77	1.77	18	1.65	1.65
5	1.88	1.88	12	1.82	1.83	19	1.72	1.71
6	1.94	1.94	13	1.89	1.89	20	1.77	1.77
7	2.00	2.00	14	1.95	1.95	21	1.83	1.83

Table 3. Validation of ANFIS model for viscosity correlation of SLS solution

No.	μ_{Data}, cP	μ_{ANFIS}, cP	No.	μ_{Data}, cP	μ_{ANFIS}, cP	No.	μ_{Data}, cP	μ_{ANFIS}, cP
1	1.30	1.30	8	1.25	1.26	15	1.15	1.14
2	1.33	1.33	9	1.29	1.29	16	1.17	1.16
3	1.38	1.38	10	1.33	1.32	17	1.19	1.20
4	1.44	1.43	11	1.36	1.35	18	1.23	1.23
5	1.51	1.51	12	1.39	1.39	19	1.28	1.28
6	1.62	1.61	13	1.44	1.44	20	1.33	1.33
7	1.70	1.70	14	1.49	1.49	21	1.39	1.38

Additionally, for concentration and temperature values within the data range, a viscosity prediction using the ANFIS model was carried out. Figure 5 shows the prediction of viscosity using the ANFIS model for changes in the concentration of methyl ester sulfonate from 0.5% to 3.0% at temperatures from 35 °C to 55 °C. The ANFIS model predicted a viscosity of 1.68 to 1.99 cP for the methyl ester sulfonate solution at 35 °C. This varied between 1.61 and 1.94 cP at 45 °C. In the meantime, the ANFIS model predicted a viscosity of 1.51 to 1.85 cP at 55 °C. Furthermore, Figure 6 includes the viscosity prediction using the ANFIS model for changes in the concentration of sodium lauryl sulfate solution from 0.5% to 3.0% at temperatures between 35 and 55. For a sodium lauryl sulfate solution at 35°C, the ANFIS model predicted viscosity between 1.29 and 1.65 cP. This varied between 1.25 and 1.43 cP for the ANFIS model at 45 °C. In the meantime, the ANFIS model predicted a viscosity of 1.16 to 1.39 cP at 55 °C.

The prediction of viscosity of the methyl ester sulfonate and sodium lauryl sulfate solutions follows the trend of measurement data where viscosity increases with increasing surfactant concentration. In addition, these models also predicted a decrease in viscosity with increasing temperature as the trend of measurement data. The correlation of the methyl ester sulfonate solution tended to be linear, while the correlation of sodium lauryl sulfate solution tended to be exponential.

An artificial neural network, another machine learning method, was used as a comparison. Viscosity predictions for the methyl ester sulfonate and sodium lauryl sulfate solutions are shown in Figures 5 and 6, respectively. Based on Figures 5 and 6, it shows that the ANFIS model tends to provide a straighter curve compared to the ANN model. The curve profile occurs for both the methyl ester sulfonate and sodium lauryl sulfate solutions. The maximum differences in the viscosity estimation of methyl ester sulfonate at temperatures of 35°C, 45°C, and 55°C between the ANN and ANFIS methods were 0.024 cP, 0.027 cP, and 0.017 cP, respectively. Meanwhile, the maximum differences in the viscosity estimation of the sodium lauryl sulfate solution at temperatures of 35°C, 45°C, and 55°C between the ANN and ANFIS methods were 0.062 cP, 0.045 cP, and 0.033 cP, respectively.

After comparing the predicted viscosity with the measured viscosity, two deviated viscosity predictions by the ANN model were identified. The viscosity prediction at a temperature of 55 °C with a concentration of 2% and 2.5% yielded a smaller value than the measured viscosity at a temperature of 60 °C with the same concentration. The difference in deviation between the prediction and measurement was quite small, namely 0.017 cP and 0.01 cP or 1.33% and 0.43%, respectively. On the other hand, all the viscosity predictions by the ANFIS model were within the possible limits. In other words, it can be said that determining viscosity with ANFIS provides better estimates compared to ANN.

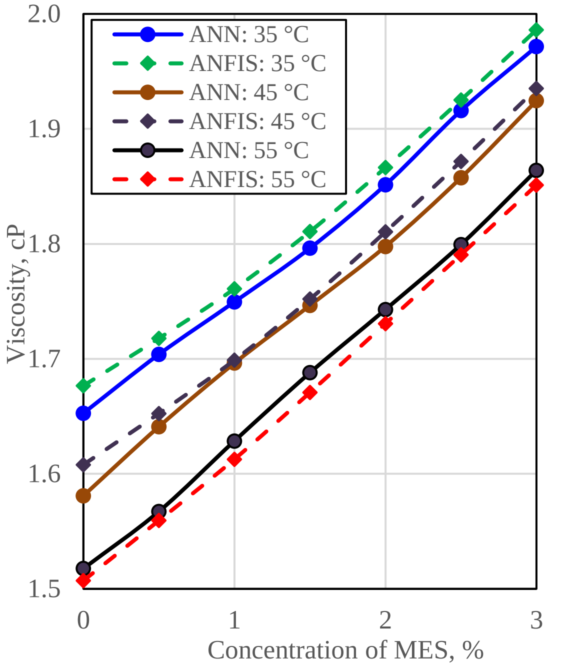

Figure 5. Viscosity prediction of methyl ester sulfonate (MES) using ANFIS and ANN as a function of concentration and temperature

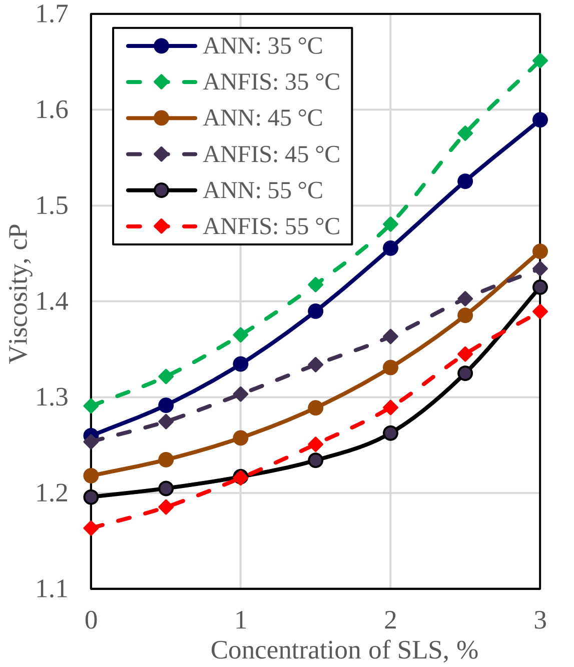

Figure 6. Viscosity prediction of sodium lauryl sulfate (SLS) using ANFIS and ANN as a function of concentration and temperature

4. Conclusions

This study demonstrated that increasing the concentration of surfactants—sodium lauryl sulfate (SLS) and methyl ester sulfonate (MES)—leads to higher solution viscosity, while increasing temperature results in viscosity reduction. The viscosity–concentration relationship was found to be more nonlinear for SLS than for MES. Both Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) models were developed to correlate viscosity data, achieving average deviations of 1.33% for MES and 0.43% for SLS. Although both models performed well, ANFIS provided superior predictive accuracy, as ANN exhibited two minor deviations from the experimental results. The originality of this research lies in applying ANFIS to model surfactant viscosity for enhanced oil recovery (EOR) applications, a field previously dominated by polymer-based studies. The proposed ANFIS framework offers an efficient and accurate data-driven approach for optimizing surfactant formulations, improving sweep efficiency, and reducing reservoir risks. Future studies may include additional parameters such as salinity, pressure, and pH to enhance the model's applicability to real reservoir conditions.

Declaration of AI and AI assisted technologies in the writing process

The authors confirm that no artificial intelligence (AI) tools or AI-assisted technologies were utilized during the preparation, drafting, or editing of this manuscript. The entire work was developed and written independently by the authors, who take full responsibility for the content of the publication.

Declaration of Competing Interest

The authors declare that there are no financial interests, personal relationships, or other circumstances that could be perceived as influencing the results or interpretations presented in this study.

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